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Evidence from the Japan Industrial Productivity Database

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Abstract

We examine the response of productivity and hours worked to technology and non-technology shocks using the Japan Industrial Productivity (JIP) Database. We find that, at the aggregate level, (1) hours worked increase in response to positive technology shocks both in the manufacturing and the nonmanufacturing sectors, which is consistent with the conventional real-business-cycle model; and (2) productivity decreases in response to positive non-technology shocks. At the two- and three-digit industry levels, we find that the correlation between productivity and hours worked in response to technology shocks still tends to be positive in the manufacturing sector while negative in the nonmanufacturing sector. Further, decomposing non-technology shocks into permanent changes in the relative size of industries and industry-specific shocks shows that the negative productivity response to non-technology shocks originates from industry-specific factors.

***Keywords**:* Technology shocks, Hours worked, Japanese economy, VAR
***JEL classification*:** E32

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1. Introduction

What is the relationship between productivity and hours worked? Real business cycle (RBC) model predicts that labor input increases in response to a favorable technology shock.[1] This is because firms demand more labor when the marginal product of labor exceeds its cost. On the other hand, based on New Keynesian models, we would expect a negative correlation between productivity and hours worked in response to a technology shock. In such models, even though a favorable technology shock lowers the marginal cost of production, firms reduce their labor input if output prices are sticky in the short run and actual demand by households as a result remains more or less unchanged. Given these conflicting theoretical predictions, an important issue is which of the two types of models is consistent with the empirical evidence on the relationship between productivity and labor input.

Against this background, the main purpose of this paper is to empirically investigate the effect of technology shocks on hours worked at both the aggregate and sectoral levels in Japan. Specifically, we conduct a comprehensive analysis on the relationship between productivity and hours worked using the Japan Industrial Productivity (JIP) Database, which contains information on total factor productivity (TFP), capital stock, hours worked, and materials for 108 industries.

There are a considerable number of macroeconomic empirical studies investigating the correlation between productivity and labor input. For instance, following the seminal study by Gali (1999), which, using a structural vector-auto regression (VAR) model, suggested that technology shocks reduce hours worked in the G7 countries except Japan, a substantial number of subsequent studies have sought to empirically examine the relationship between productivity and employment in the United States. Studies confirming Gali's (1999) results for the U.S. economy include Francis and Ramey (2009) and Gali (2005). Shea (1998) found a negative correlation between productivity and hours worked using alternative measures of technology such as patents and R&D, while Basu, Fernald, and Kimball (2004) similarly found a negative correlation, identifying aggregate technology by estimating a Hall-style regression equation.[2]

Further, with the growing availability of industry- and firm-level data, there has also been a considerable increase in studies on the relationship between productivity and employment at disaggregate levels. For instance, using 4-digit manufacturing sector data for the United States,

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[1] See, for example, Cooley and Prescott (1995) among others.

[2] Other studies, in contrast, suggest that hours worked increase rather than decrease in response to positive technology shocks. Christiano, Eichenbaum, and Vigfusson (2003), for example, find that hours increase when the hour variable is estimated in a level form. We investigate this issue in Appendix C.

Chang and Hong (2006) found that technology improvements raise employment in more industries than they lower employment. On the other hand, using U.S. firm-level data, Franco and Philippon (2007) found a negative correlation between productivity and employment in response to a technology shock. Meanwhile, Kim and Chun (2011) found that firms in industries with low inventory-sales ratios employ more workers in response to a favorable technology shock, while those with high inventory-sales ratios employ fewer workers. In contrast, using Italian firm-level data for the manufacturing sector, Marchetti and Nucci (2007) observed that the contractionary effect was stronger for firms with stickier prices, and weaker or not significant for firms with more flexible prices. A contractionary labor input response to technology shocks is also found by Carlsson and Smedsaas (2007) using Swedish firm-level data.

Studies on Japan investigating the relationship between productivity and hours worked have used aggregate-level data. For example, employing a sign-restriction VAR, Braun and Shioji (2004) found that hours worked increased in response to favorable technology shocks. Estimating a time-varying-parameter VAR model, Ko and Murase (2012) found that hours worked increased in most of the sample periods in response to positive technology shocks. In contrast, using an aggregate technology measure they constructed from industry-based data, Miyagawa, Sakuragawa, and Takizawa (2006) found the relationship between positive technology shocks and labor input to be negative. However, none of the existing studies for Japan investigates whether the aggregate-level results can also be observed at disaggregate levels. Furthermore, to the best of our knowledge, there are no studies to date investigating the relationship between productivity and hours worked outside the manufacturing sector - be it in Japan, the United States, or any of the other G7 countries.

Given this, the key aim of this paper is to examine the relationship between productivity and hours worked at both the aggregate and disaggregate levels. Furthermore, we investigate whether there are any differences between manufacturing and nonmanufacturing industries, an issue which the existing literature so far has ignored. Our analysis using the JIP Database suggests that, at the aggregate level, hours worked increase in response to positive technology shocks. While this finding is not new, what is new is that our investigation indicates that this applies to both the manufacturing and the nonmanufacturing sector. This positive effect on labor by technology shocks is consistent with RBC models. Furthermore, we find that productivity decreases in response to nontechnology shocks.

The results at the 2-digit and 3-digit industry levels, however, indicate that the size and sign of the impact on labor input of a positive technology shock differs across industries. Specifically, when a favorable technology shock hits the economy, more manufacturing industries show a positive short-run response of hours worked than a negative response. Specifically, a significant increase in labor input in response to a positive technology shock can be observed in the "fabricated metal products," "machinery," and "precision instruments" industries.

On the other hand, for the nonmanufacturing sector we find that hours worked decline in most industries, despite the finding mentioned above that hours worked increase at the aggregate level. The negative correlation is particularly large in “agriculture, forestry, and fishing,” “mining,” “real estate,” “communications,” and “personal services.” Overall, the positive co-movement of productivity and hours in the majority of manufacturing industries is consistent with standard RBC models, while the negative co-movement in the majority of nonmanufacturing industries is more consistent with New Keynesian models.

Furthermore, we investigate the source of the negative correlation between productivity and hours worked in response to nontechnology shocks. Decomposing nontechnology shocks into composition shocks and industry-specific shocks, our investigation provides a novel explanation of this negative correlation. Specifically, composition shocks are defined as shocks that permanently increase the size of a certain industry relative to other industries, which may reflect a permanent change in consumer preferences. On the other hand, industry-specific shocks are defined as shocks that affect neither the relative size of an industry nor its long-run productivity. We find that in the case of both types of shocks, hours worked increase permanently, but the productivity and share responses differ somewhat. The findings of the decomposition analysis can be summarized as follows: (1) in response to technology and composition shocks, the share of the industry concerned increases permanently both in the manufacturing and the nonmanufacturing sector; (2) in response to positive composition shocks, hours worked in the industry clearly increase in the manufacturing sector, reflecting labor reallocation across industries; however, in the nonmanufacturing sector, such a response is almost absent; (3) the findings lead us to conclude that the observed negative correlation between productivity and hours worked in response to nontechnology shocks is due to industry-specific factors.

The remainder of the paper is organized as follows. Section 2 describes the VAR model and the data we use for our analysis. Section 3 then presents our results, starting with those for the aggregate economy, followed by the results at the 2-digit industry level, and finally those of the decomposition analysis. Section 4 concludes.

2. Empirical Framework

This section presents the empirical framework of our analysis. We describe how we identify technology shocks using a VAR model and how we construct our data.

2.1 Bivariate VAR model

We assume that the VAR model can be written in the following vector moving average (VMA) form:

$$x_t = C(L)\varepsilon_t$$

where x_t is defined as $x_t \equiv [\Delta z_t, \Delta h_t]'$ with z_t and h_t denoting productivity and labor input (both in logarithms). $C(L)$ is an infinite polynomial matrix. Following Chang and Hong (2006), we use measured TFP, denoted by z_t^{tfp}, as the first dependent variable to capture technology shocks.[3] We assume that the vector of the structural shocks, $\varepsilon_t \equiv \varepsilon_t^T, \varepsilon_t^{NT}]'$, has the identity covariance matrix *I*. ε_t^T and ε_t^{NT} represent technology and nontechnology shocks, respectively. To identify structural shocks in the VAR scheme, we employ the long-run restriction introduced by Gali (1999), that is, only technology shocks may affect productivity in the long run.[4]

2.2 Data

For the estimation, we employ annual data for the period 1974-2007. Aggregate and 3-digit industry data on TFP, labor input, and output are taken from the JIP 2011 Database. The database provides information on 108 industries in the market and nonmarket sectors of the economy. Here, we only focus on the market economy, consisting of 92 industries. Furthermore, we aggregate the 3-digit data for these 92 industries to 2-digit industry data, leaving us with 28 industries. These 28 industries can be grouped into manufacturing and nonmanufacturing industries, with the former comprising 15 and the latter 13 industries.

As for output, we use gross output in our benchmark estimation and reexamine the results using value-added instead. The labor input variable is obtained by multiplying the number of employees by working hours. TFP is the dependent variable to identify technology shocks. As an alternative measure of productivity, labor productivity is constructed by dividing gross output by man-hours.

3. Results

3.1 Aggregate economy

We start by examining the impulse responses in our benchmark VAR model. Figure 1 presents the impulse responses of TFP and hours worked. The responses to technology shocks are shown in the two top panels, while those to nontechnology shocks are shown in the two bottom panels. The results

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[3] Chang and Hong (2006) argue that TFP is a more natural measure of technology because labor productivity reflects the input mix as well as efficiency. Under constant returns to scale, labor productivity growth can be expressed as TFP growth and input deepening such as an increase in the capital-labor ratio.

As a robustness check, we also use labor productivity instead of TFP as an alternative variable. See Appendix B for more details.

[4] In Appendix D, following Uhlig (2005) and Braun and Shioji (2004) we impose sign restrictions as an alternative identification scheme.

indicate that in response to a one-standard-deviation technology shock, TFP in the whole market economy increases by 0.60 percent at impact and converges to the new steady state level, 1.00 percent higher than before. Hours worked show procyclical movements, increasing 0.20 percent at impact and continuing to slowly increase to the new steady state, 0.58 percent higher than before. This implies that technology shocks have an expansionary effect on output even in the short run. The results further indicate that the responses to a technology shock in the manufacturing sector are much larger than those in the nonmanufacturing sector. What is more, although the point estimate of the hours worked response in the nonmanufacturing sector is positive, it is not significant. Therefore, our empirical results based on the aggregate data for Japan are consistent with those obtained by Gali (1999) and Braun and Shioji (2004), and support the RBC model. Furthermore, we find that the positive correlation between TFP and hours worked holds in both the manufacturing and nonmanufacturing sectors, which has not been shown for Japan and other countries before.

Next, turning to nontechnology shocks, we find that the TFP response is countercyclical. Specifically, TFP decreases by 0.21 percent, which may reflect countercyclical factor utilization, and returns to the previous level over time. In contrast, hours worked initially increase by 0.28 percent. Finally, the impulse responses of the manufacturing and nonmanufacturing sector show similar patterns.

[Insert Figure 1]

Table 1 reports the estimates of both the unconditional and conditional correlations between the growth rates of TFP and hours worked at the aggregate level. The first column shows that the estimates of the unconditional correlation between these two variables are positive and significant for the market economy overall and for the manufacturing sector. Next, the second and the third columns show the correlations conditional on technology and nontechnology shocks. The results show a clear pattern: in the case of technology shocks, the sign on the correlation between TFP and hours worked is positive in all cases and statistically significant for the market economy overall and the manufacturing sector, while in the case of nontechnology shocks, the sign is negative in all cases, although the results are not significant.

[Insert Table 1]

3.2 2-digit industry level

Next, we examine whether the findings at the aggregate level still hold at the industry level. To do so, we re-estimate the VAR using the 2-digit industry data. The bivariate VMA representation for each industry *i* is as follows:

$$\mathrm{x_{it}} = \mathrm{C_i(L)}\varepsilon_{\mathrm{it}}, \quad \text{for } \mathrm{i} \in \{1, \cdots, 28\},$$

where $\mathrm{x_{it}}$ is defined as $\mathrm{x_{it}} \equiv [\Delta \mathrm{z_{it}}, \Delta \mathrm{h_{it}}]'$ with $\mathrm{z_{it}}$ and $\mathrm{h_{it}}$ denoting productivity and hours worked in industry *i*. The impulse responses of TFP and hours worked at the 2-digit industry level are shown in Figure 2. The upper panels (Figure 2(a)) display the responses to technology shocks, while the lower panels (Figure 2(b)) display those to nontechnology shocks. The top two panels in Figure 2(a) show the median responses of the market economy overall, the manufacturing sector, and the nonmanufacturing sector, represented by the black solid, circled blue, and diamond red lines, respectively.[5]

Looking at TFP first, we find that in response to a one-standard-deviation technology shock, the impact responses of TFP are around 2 percent in all cases. In contrast to the result when using aggregate data, the increase of TFP in the nonmanufacturing sector is higher than that in the manufacturing sector. The reason for this difference is that the response shown here presents the simple mean, which implies that all industries receive equal weights. On the other hand, the aggregate benchmark case presents the weighted-sum responses, so that industries that are larger or where movements are more volatile make a larger contribution to the aggregate impulse responses.

The results for hours worked show that the responses clearly differ in the two sectors. Specifically, while the median response of hours worked to technology shocks is positive in the market economy overall and in the manufacturing sector, it is negative in the nonmanufacturing sector. Next, the middle and bottom panels of Figure 2(a) show the distributions of the impact responses and the size of impact in each industry. We find that in the manufacturing sector nine of the 15 industries show a positive response, while in the nonmanufacturing sector eight of the 13 industries exhibit a negative response. The result for the nonmanufacturing sector is more consistent with New Keynesian models, while that for the manufacturing sector is more consistent with RBC models.

Turning to nontechnology shocks, different from the aggregate case, the TFP response in the market economy is positive. Further, looking at the results for the manufacturing sector and the nonmanufacturing sector, on average, the impact response of TFP is positive in the former and

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[5]The median response here refers to the response of the industry that represents the median. For example, the black so lid line shows the response of the 15th industry of the 28 industries in the market economy overall. Similarly, the other lines show the response of the 8th of the 15 industries in the manufacturing sector and of the 7th of the 13 industries in the nonmanufacturing sector.

negative in the latter.[6]

[Insert Figure 2]

Table 2 shows how many industries display a positive or negative response in the short run. Part (a) shows the number of industries for which the response of hours worked to a technology shock is positive or negative. At the 2-digit level, 12 industries show a positive response at impact. In the manufacturing sector, seven industries show a positive response, and the response is statistically significant in two industries. On the other hand, in the nonmanufacturing sector, eight industries show a negative response, which is statistically significant for two industries. One year after the shock, this pattern becomes more pronounced. Specifically, the hours-worked response is positive in 10 industries in the manufacturing sector and significantly so in four, while it is negative in seven industries in the nonmanufacturing sector statistically so in three. The pattern is also more pronounced at the 3-digit level. The contemporaneous response of hours worked is positive in 37 manufacturing industries (and significantly so in 8) and negative in 24 industries in the nonmanufacturing sector (significantly so in 15). Part (b) of the table shows the TFP response to a nontechnology shock. At the 2-digit level, TFP decreases contemporaneously in 12 industries (significantly so in three). At the 3-digit level, the negative response of industry TFPs becomes more notable. 44 industries show a negative response, and this negative response is significant in 11 industries.

[Insert Table 2]

Tables 3 and 4 show the unconditional and conditional correlations between the growth rates of TFP and hours worked. Table 3, which presents the results for the manufacturing sector, the correlation conditional on technology shock ranges from -0.947 in “transport equipment” to 0.98 in “machinery.” The correlation is positive in nine of the 15 manufacturing industries, although it is significant in only three: “fabricated metal products,” “machinery,” and “precision instruments” industries show a statistically significant increase of labor input when positive technology shocks occur. The correlation is negative, but not significant, in the remaining six industries: “pulp, paper, and paper products,” “chemicals,” “petroleum and coal products,” “basic metal,” “non-ferrous metal products,” and “transport equipment.”

On the other hand, Table 4 for the nonmanufacturing sector shows that in this sector hours worked

[6]We arrive at similar findings using 3-digit industry data. The impulse responses at the 3-digit level can be obtained from the authors on request.

declined in more sectors than they increased. Specifically, the correlation is negative in eight industries, and significantly so in five: “agriculture, forestry, and fishing,” “mining,” “real estate,” “communications,” and “personal services.”[7] Turning to the results for nontechnology shocks, the correlation appears to be negative in eight out of 13 industries, although the negative correlation is significant in only two (electricity, gas, and water supply; retail trade).

[Insert Tables 3 and 4]

Let us now compare our results based on aggregate data and those based on industry-level data. In the aggregate case, we found two things: (1) both TFP and hours worked moved procyclically in response to technology shocks; (2) in contrast, in the case of nontechnology shocks, hours worked also responded procyclically, but TFP responded countercyclically. However, we find that the pattern observed at the aggregate level does not necessarily hold at the industry level. Specifically, in the case of technology shocks, hours worked in the nonmanufacturing sector generally responded countercyclically, while in the case of nontechnology shocks, TFP in the manufacturing sector generally responded procyclically. In other words, the responses are the direct opposite. Another interesting finding is that regardless of the nature of the shocks (i.e., whether they are technology or nontechnology shocks) the positive correlation between TFP and hours worked in the manufacturing sector and the negative correlation between the two in the nonmanufacturing sector holds. This comovement potentially explains why the unconditional correlations among output, TFP, and hours worked are higher in the manufacturing sector than in the nonmanufacturing sector.

Next, we examine what lies behind the differences between the manufacturing and the nonmanufacturing sector. The positive correlation in the manufacturing sector may reflect the fact that manufacturing firms are exposed to competition in the global economy. The competitive pressures in this sector may impel firms to employ more workers whenever they face technological innovation. On the other hand, the negative correlations in the nonmanufacturing sector may reflect market distortions.[8] Ahearne and Shinada (2005) suggest that in Japan, competition in markets for non-traded goods and in service industries is suppressed due to the presence of cartels, excessive government regulation, and other market distortions. Similarly, Fukao (2007) highlights distortions in Japan's nonmanufacturing sectors arising from regulatory barriers and bank bailouts of de-facto

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[7] A noteworthy result is that in some industries such as “wholesale,” “retail trade,” and “finance and insurance,” the positive correlation is near unity, although it is significant only in the case of “retail trade.” These industries may be the source for the positive correlation for the nonmanufacturing sector at the aggregate level.

[8] It is difficult to test whether sticky prices are the exact reason for the negative correlations in the nonmanufacturing sector, because we do not have data on the frequency of price changes in each sector. We leave this issue for future research.

bankrupt companies, while Caballero, Hoshi, and Kashyap (2008) find that the so-called zombie problem in the 1990s – de-facto bankrupt companies were being artificially kept afloat through bank bailouts – was more serious in the nonmanufacturing than the manufacturing sector. Finally, Inui and Kwon (2005) point out that markup rates in the nonmanufacturing sector were higher than those in manufacturing sector. All these studies suggest that Japan’s nonmanufacturing sector in particular is subject to a variety of distortions, which may be the cause of the negative correlations observed in the nonmanufacturing sector.

3.3 Decomposition of nontechnology shocks

The next question we address is what causes the negative TFP response in Japan to nontechnology shocks. Specifically, we look for the source of the negative correlation between labor input and productivity by decomposing nontechnology shocks into permanent changes in the composition of aggregate output and industry-specific shocks. Changes in the composition of aggregate output may result from changes in consumer tastes, which determine the relative consumption-weight of specific industries within the total consumption bundle, which in turn translates into changes in the relative demand for the different industries. For example, the relative size of agriculture has been decreasing, while that of the automobile industry has been increasing. Ahearne and Shinada (2005) suggest that industries such as “construction,” “wholesale,” and “retail trade” expanded rapidly in the 1980s and their weights in the economy overall remained more or less unchanged during the 1990s despite poor productivity growth. On the other hand, industry-specific shocks are shocks that do not have any impact on any of the other industries. In order to identify these two shocks, we employ long-run restrictions in a structural VAR model. Specifically, we define sector-specific shocks as shocks that do not have a permanent effect on an industry’s productivity and share in the economy, and composition shocks as shocks that do not have a permanent effect on productivity.[9]

The trivariate VMA representation for each industry *i* can be written as

$$x_{it} = C_i(L)\varepsilon_{it}, \text{ for } i \in \{1, \cdots, 28\},$$

where x_{it} is now defined as $x_{it} \equiv [\Delta z_{it}, \Delta m_{it}, \Delta h_{it}]'$ and m_{it} denotes the relative size of industry *i* defined as

$$m_{it} \equiv \frac{y_{it}}{\sum_{i=1}^{28} y_{it}},$$

[9] These definitions are very similar to those employed by Franco and Philippon (2007), who investigate the role of permanent and transitory technology shocks in firm dynamics.

where y_{it} is the gross output in sector *i*. Only shocks that influence productivity in the long run are defined as technology shocks, while composition shocks have no long-run effect on productivity. Moreover, industry-specific shocks are shocks that have no long-run effect on either productivity or the relative size of the industry.

Figure 3 shows the results when we distinguish between these three types of shocks, i.e., technology shocks and two types of nontechnology shocks, namely composition and industry-shocks. We start with the response to a technology shock (Figure 3(a)). As can be seen, the responses of TFP and hours worked are almost the same as those in the bivariate VAR case. Furthermore, we find that technology shocks permanently increase the relative size of the corresponding industry in both the manufacturing and the nonmanufacturing sector. In other words, when a positive technology shock hits the economy, many industries in the manufacturing sector increase hours worked, and this is associated with a permanent increase of the share of such industries. On the other hand, for the nonmanufacturing sector, we find that hours worked move in the opposite direction, i.e., they decrease in industries experiencing a positive technology shock, even though the share of such industries increases.

Next, we examine the responses to a composition shock (Figure 3(b)). First, on average, composition shocks permanently increase the share of an industry by around three percent in all cases and are accompanied by a transitory increase in TFP. In other words, there is no counter-cyclical relationship between the industry share and TFP in the case of composition shocks. Second, hours worked in all cases show a permanent increase, which may reflect the reallocation of labor across industries. Third, however, the response of hours worked is smaller than the industry share response. In the manufacturing sector, the median industry share response on impact is 2.5 percent, which is 0.5 percentage points higher than that in the nonmanufacturing sector, but the responses subsequently converge to almost the same steady state. In contrast, the effect on hours worked differs for the two sectors. While in the manufacturing sector, hours worked increase by 2 percent on impact and eventually permanently increase by 2.5 percent, the response in the nonmanufacturing sector is around 0.5 percent on impact and subsequently remains more or less unchanged. Therefore, we conclude that the labor reallocation is more active in the manufacturing sector.

Finally, we examine the responses to industry-specific shocks (Figure 3(c)). We find that the magnitudes of the responses in the manufacturing sector and the nonmanufacturing sector differ considerably. Specifically, we find that while the TFP response is negative in both sectors, it is much more pronounced in the nonmanufacturing sector. On the other hand, the share response is close to zero in the nonmanufacturing sector, while it is substantially negative in the manufacturing sector.

In sum, the decomposition of nontechnology shocks reveals that the negative response of TFP to nontechnology shocks has its origins in industry-specific factors. In other words, the negative correlation between TFP and hours worked in the case of nontechnology shocks does not spill over to other industries, and hence does not change industry shares.

[Insert Figure 3]

Table 5 shows the number of industries for which the impact response of each variable to the different types of shocks is positive or negative in the trivariate VAR model. Part (a) shows the number of industries whose impact response in terms of the industry share and hours worked to a technology shock was positive or negative. As shown in Figure 3, a favorable technology shock in an industry generally increases the share of the corresponding industry. Table 5 indicates that this was the case in 13 industries in the manufacturing sector, and the increase in the industry share was statistically significant in 9 industries. Similarly, in the nonmanufacturing sector increase, the shares of 11 industries increased, and the increase was statistically significant in nine. Turning to part (b) of the table, we find that in response to a composition shock, TFP and hours worked increase in most industries. Specifically, in the manufacturing sector, employment increased in 14 industries and the increase is significant in 10.

The much more responsive movement of labor across industries in the manufacturing sector may reflect the fact that in Japan, as discussed earlier, manufacturing sectors are exposed to much greater competition than nonmanufacturing industries.

[Insert Table 5]

4. Conclusion

In this paper, focusing on Japan, we investigated whether technology shocks increase or decrease hours worked both at the aggregate and industry levels. Regardless of the productivity measure used, we found that a positive relationship between productivity and hours worked in the case of technology shocks is observed in the aggregate data, which is consistent with the RBC model. However, using 2-digit industry level data, we found that in many nonmanufacturing industries, a negative relationship could be observed, which is more consistent with New Keynesian models.

We also investigated the source of the negative relationship between productivity and hours worked that we found in the case of nontechnology shocks. Our results based on industry data show that the responses to such shocks differed somewhat in the manufacturing and the nonmanufacturing sector. Specifically, we found that the negative correlation could also be observed at the 2-digit industry level for nonmanufacturing industries, but not for manufacturing industries.

To discover the source of the negative correlation between TFP and hours worked in the case of nontechnology shocks, we decomposed nontechnology shocks into changes in industry composition and industry-specific shocks. Doing so, we found that the source of the negative correlation in the case of nontechnology shocks is industry-specific shocks rather than permanent changes in the composition of output.

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Table 1: (Un)conditional correlation between TFP and hours worked

Industry	$cor(\Delta z^{tfp}, \Delta h)$	$cor(\Delta z^{tfp}, \Delta h \vert \varepsilon^{T})$	$cor(\Delta z^{tfp}, \Delta h \vert \varepsilon^{NT})$
Market economy	0.427**	0.926**	-0.632
	(0.189)	(0.297)	(0.414)
Manufacturing	0.526**	0.835**	-0.601
	(0.145)	(0.227)	(0.605)
Nonmanufacturing	0.020	0.972	-0.503
	(0.185)	(0.707)	(0.424)

Note: Standard errors of the covariance estimates are given in parentheses. Double asterisks indicate statistical significance at the 5 percent level. $cor(\Delta z^{tfp}, \Delta h)$ denotes the unconditional correlation between TFP and hours worked, while $cor(\Delta z^{tfp}, \Delta h|\varepsilon^{T})$ and $cor(\Delta z^{tfp}, \Delta h|\varepsilon^{NT})$ denote correlations conditional on technology and nontechnology shocks, respectively.

Table 2: Short-run responses
Bivariate VAR case

	Market economy		*Manufacturing*		*Nonmanufacturing*	
Data	Positive	Negative	Positive	Negative	Positive	Negative
(a) Hours response to a technology shock						
2-digit						
Impact	12	16	7	8	5	8
	(2)	(2)	(2)	(0)	(0)	(2)
1 year later	16	12	10	5	6	7
	(5)	(3)	(4)	(0)	(1)	(3)
3-digit						
Impact	53	39	37	15	16	24
	(13)	(18)	(8)	(3)	(5)	(15)
1 year later	46	46	32	20	14	26
	(15)	(17)	(11)	(3)	(4)	(14)
(b) TFP response to a nontechnology shock						
2-digit						
Impact	16	12	11	4	5	8
	(3)	(3)	(2)	(2)	(1)	(1)
1 year later	16	12	12	3	4	9
	(0)	(2)	(0)	(1)	(0)	(1)
3-digit						
Impact	48	44	25	27	23	17
	(8)	(11)	(3)	(5)	(5)	(6)
1 year later	46	46	27	25	19	21
	(4)	(4)	(1)	(2)	(3)	(2)

Note: The table shows the number of industries for which short-run response of hours worked (TFP) to a technology (nontechnology) shock is positive or negative. The number of industries for which the increase or decrease is significant at least at the 10 percent level is given in parentheses.

Table 3: (Un)conditional correlation using 2-digit industry data
Manufacturing industries

Code	Industry	$cor(\Delta z^{tfp}, \Delta h)$	$cor(\Delta z^{tfp}, \Delta h \vert \varepsilon^{T})$	$cor(\Delta z^{tfp}, \Delta h \vert \varepsilon^{NT})$
3	Food products and	-0.020	0.224	-0.536
	beverages	(0.166)	(0.406)	(0.409)
4	Textiles	0.165	0.739	-0.664**
		(0.223)	(0.497)	(0.269)
5	Pulp, paper and	-0.004	-0.406	0.647
	paper products	(0.166)	(0.629)	(0.594)
6	Chemicals	-0.104	-0.570	0.701
		(0.214)	(0.661)	(0.702)
7	Petroleum and	-0.090	-0.824	0.600
	coal products	(0.173)	(0.514)	(0.493)
8	Nonmetallic mineral	-0.190	0.595	-0.750**
	products	(0.170)	(0.665)	(0.312)
9	Basic metal	0.252	-0.850	0.618**
		(0.161)	(0.615)	(0.162)
10	Nonferrous metal products	-0.080	-0.661	0.616
		(0.197)	(0.518)	(0.458)
11	Fabricated metal products	0.375**	0.623*	0.669
		(0.137)	(0.365)	(0.626)
12	Machinery	0.686**	0.980**	0.773
		(0.115)	(0.171)	(0.612)
13	Electrical machinery,	0.201	0.700	0.634
	equipment and supplies	(0.217)	(0.792)	(0.454)
14	Transport equipment	-0.048	-0.947	0.595
		(0.141)	(0.611)	(0.504)
15	Precision instruments	0.599**	0.854**	0.620
		(0.119)	(0.153)	(0.609)
16	Publishing and printing	-0.006	0.557	-0.534
		(0.196)	(0.685)	(0.474)
17	Others	0.257	0.065	0.628**
		(0.172)	(0.569)	(0.296)

Note: Standard errors of the covariance estimates are given in parentheses. Double (single) asterisks indicate statistical significance at the 5 (10) percent level. $cor(\Delta z^{tfp}, \Delta h)$ denotes the unconditional correlation between TFP and hours worked, while $cor(\Delta z^{tfp}, \Delta h|\varepsilon^{T})$ and $cor(\Delta z^{tfp}, \Delta h|\varepsilon^{NT})$ denote correlations conditional on technology and nontechnology shocks, respectively.

Table 4: (Un)conditional correlation using 2-digit industry data
Nonmanufacturing industries

Code	Industry	$cor(\Delta z^{tfp}, \Delta h)$	$cor(\Delta z^{tfp}, \Delta h \vert \varepsilon^{T})$	$cor(\Delta z^{tfp}, \Delta h \vert \varepsilon^{NT})$
1	Agriculture, forestry	-0.241	-0.673*	0.688
	and fishing	(0.177)	(0.355)	(0.639)
2	Mining	-0.103	-0.949*	0.681**
		(0.211)	(0.485)	(0.329)
18	Construction	-0.022	0.546	-0.524
		(0.168)	(0.693)	(0.383)
19	Electricity, gas and	-0.399**	-0.554	-0.682*
	water supply	(0.144)	(0.466)	(0.411)
20	Wholesale	0.326	0.955	0.645
		(0.202)	(0.704)	(0.594)
21	Retail trade	0.207	0.940**	-0.743*
		(0.196)	(0.477)	(0.426)
22	Finance and insurance	0.028	0.916	-0.559
		(0.209)	(0.749)	(0.513)
23	Real estate	-0.398**	-0.876**	0.698
		(0.173)	(0.299)	(0.502)
24	Transport	-0.257	-0.435	-0.742
		(0.164)	(0.692)	(0.573)
25	Communications	-0.145	-0.994*	0.833
		(0.183)	(0.591)	(0.770)
26	Public services	0.075	0.825	-0.786
		(0.253)	(0.704)	(0.647)
27	Business services	-0.226	-0.432	-0.683
		(0.175)	(0.610)	(0.591)
28	Personal services	-0.428**	-0.877*	-0.632
		(0.149)	(0.475)	(0.611)

Note: Standard errors of the covariance estimates are given in parentheses. Double (single) asterisks indicate statistical significance at the 5 (10) percent level. $cor(\Delta z^{tfp}, \Delta h)$ denotes the unconditional correlation between TFP and hours worked, while $cor(\Delta z^{tfp}, \Delta h|\varepsilon^{T})$ and $cor(\Delta z^{tfp}, \Delta h|\varepsilon^{NT})$ denote correlations conditional on technology and nontechnology shocks, respectively.

Table 5: Impact responses using 2-digit industry data
Trivariate VAR case

	Market economy		*Manufacturing*		*Nonmanufacturing*	
Data	Positive	Negative	Positive	Negative	Positive	Negative
(a) Technology shock						
Share	24	4	13	2	11	2
	(18)	(0)	(9)	(0)	(9)	(0)
Hours worked	12	16	7	8	5	8
	(2)	(2)	(1)	(0)	(1)	(2)
(b) Composition shock						
TFP	19	9	12	3	7	6
	(3)	(2)	(3)	(1)	(0)	(1)
Hours worked	22	6	14	1	8	5
	(14)	(1)	(10)	(0)	(0)	(2)
(c) Industry-specific shock						
TFP	11	17	7	8	4	9
	(2)	(4)	(1)	(1)	(1)	(3)
Share	9	19	3	12	6	7
	(4)	(5)	(0)	(4)	(4)	(1)

Note: The table shows the number of industries for which the impact response of each variable to a particular shock is positive or negative. The number of industries for which the increase or decrease is significant at least at the 10 percent level is given in parentheses.

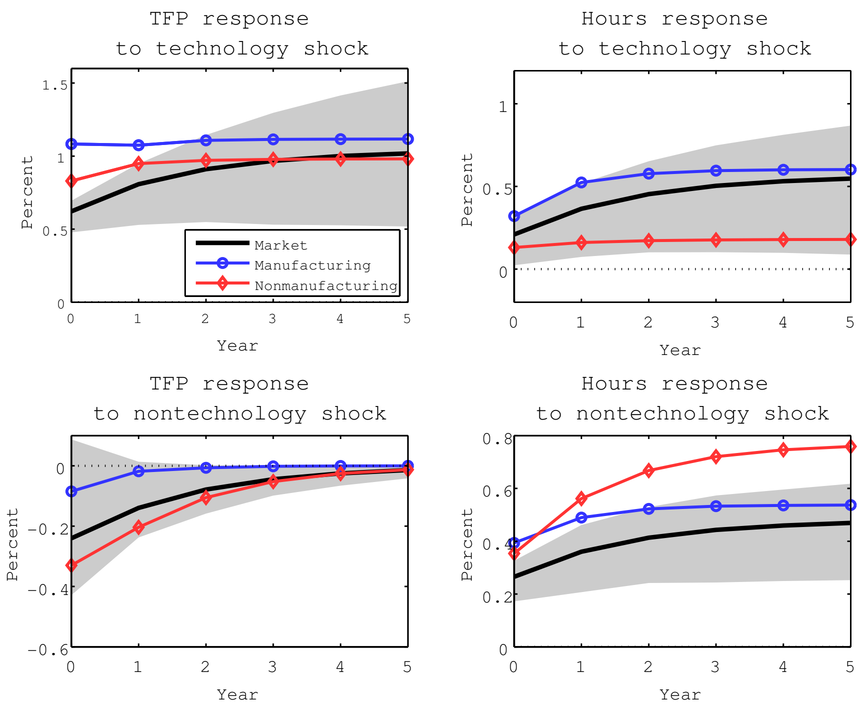
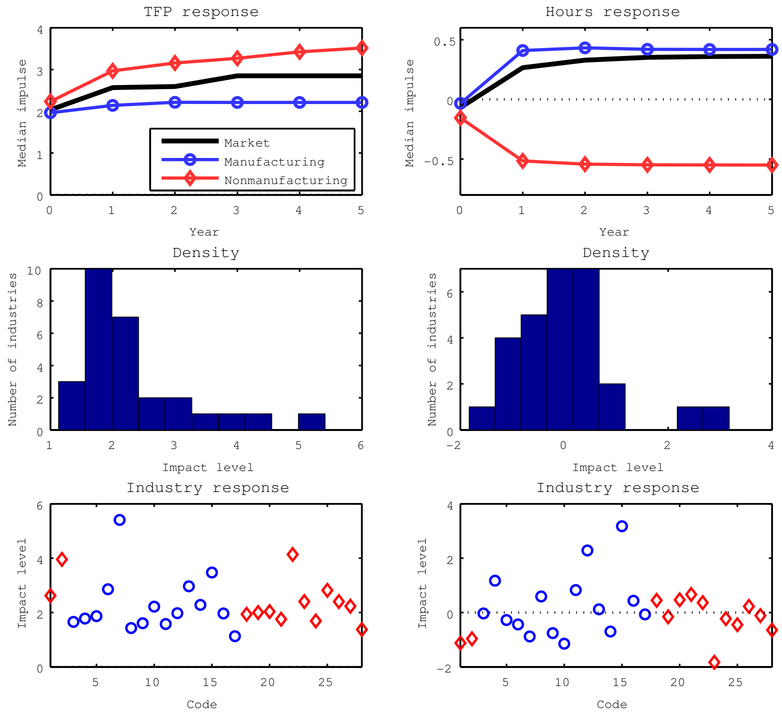


Figure 1. Impulse responses of TFP and hours worked.

Note: The thick black, blue circled, red diamond lines indicate the responses of the aggregate economy, the manufacturing sector, and the nonmanufacturing sector, respectively. The shaded areas represent the 90-percent confidence intervals.

(a) Responses to technology shock



(b) Responses to nontechnology shock

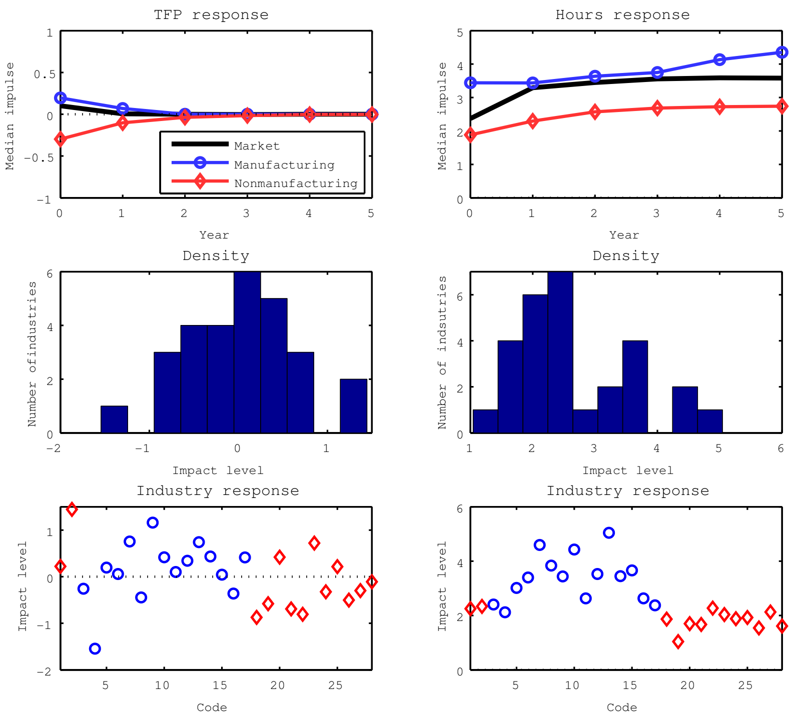
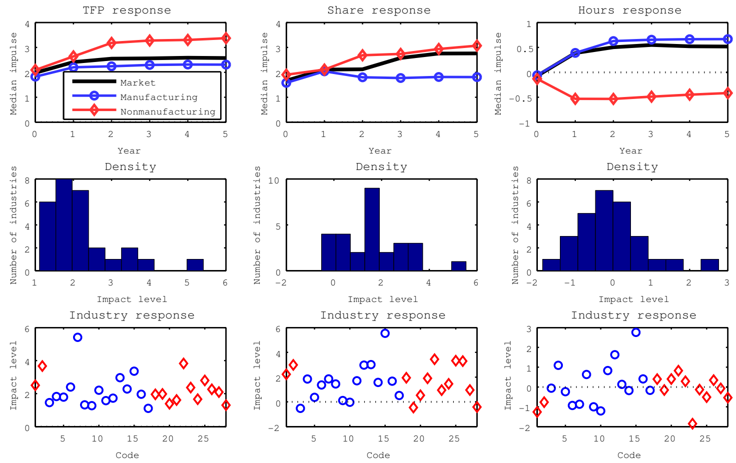
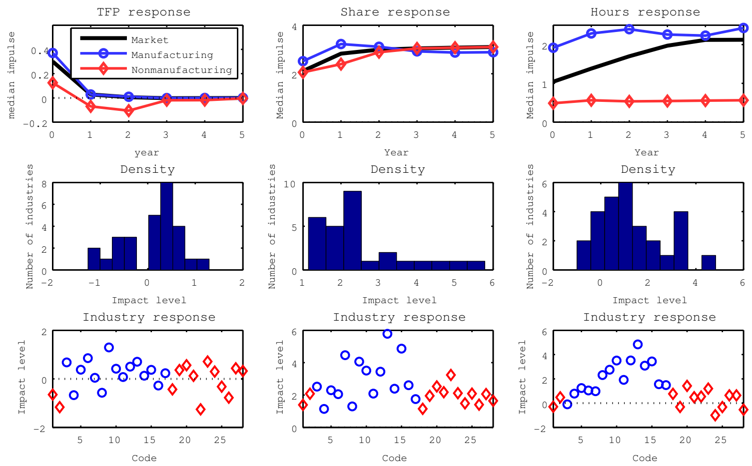


FIGURE 2. Sectoral impulse responses to (a) technology shocks and (b) nontechnology shocks

(a) Responses to technology shock



(b) Responses to composition shock



(c) Responses to industry-specific shock

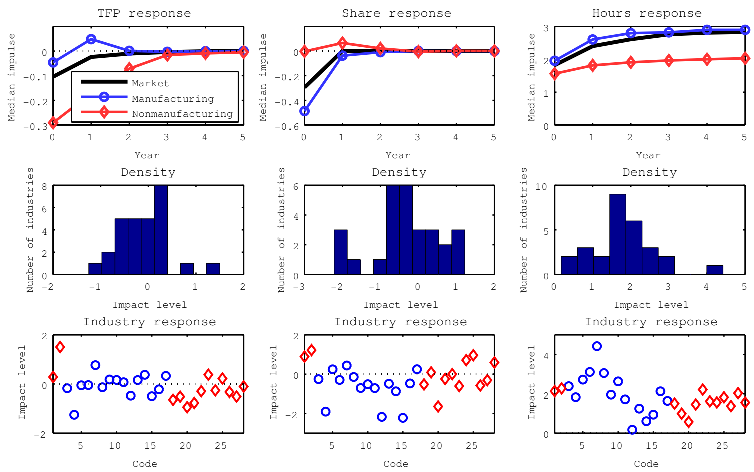


FIGURE 3. 2-digit industry impulse responses to (a) technology shocks, (b) composition shocks, and (c) industry-specific shocks

Appendix A: Stationarity of data

In this appendix, we show the results of an ADF unit root test on key variables at the 2-digit industry level. In the case of the logarithm of hours worked, we can reject the null of the unit root at the 10, 5, and 1 percent confidence levels for 2, 1, and 0 industries, respectively. The ADF test on the first difference of the same series rejects 28, 26, and 23 industries at 10, 5, and 1 percent confidence levels, respectively. Next, for the logarithm of industry shares, we can reject the null of the unit root for 8, 6, and 2 industries, at the 10, 5, and 1 percent confidence levels, respectively. Further, the ADF test on the first difference reject the null of the unit root for 27, 24, and 21 industries at the 10, 5, and 1 percent confidence levels. The results suggest that for the majority of industries the series of variables are I(1). We perform the ADF test on the first difference of TFP because the JIP database only offers the growth rate of TFP. We can reject the null of the unit root for 6, 4, and 2 industries at the 10, 5, and 1 percent confidence levels, respectively.

Appendix B: Labor productivity measure

Chang and Hong (2006) find that, in the United States, manufacturing sector TFP and labor productivity behave quite differently over time. In particular, there are shocks that affect labor productivity in the long run that do not involve changes in TFP. To investigate whether the same applies to Japan, we investigate whether TFP and labor productivity in Japan's manufacturing and nonmanufacturing sector also behave differently in response to shocks. Following Galí (1999), we use labor productivity to identify technology shocks. Table A3 and Figures A2 display the estimation results at the aggregate level. For the aggregate level, in Table A3 and Figure A2, we find very similar results to the benchmark case: hours worked increase in response to technology shocks, while productivity decrease in response to nontechnology shocks.

Table A1: (Un)conditional correlation between labor productivity and hours worked

Industry	$cor(\Delta z^{lp}, \Delta h)$	$cor(\Delta z^{lp}, \Delta h \vert \varepsilon^T)$	$cor(\Delta z^{lp}, \Delta h \vert \varepsilon^{NT})$
Market economy	0.793**	1.000**	-0.737
	(0.110)	(0.022)	(0.524)
Manufacturing	0.857**	0.991**	0.792
	(0.075)	(0.027)	(0.720)
Nonmanufacturing	0.460**	1.000**	-0.774
	(0.199)	(0.285)	(0.496)

Note: Standard errors of the covariance estimates are given in parentheses. Double asterisks indicate statistical significance at the 5 percent level. $cor(\Delta z^{lp}, \Delta h)$ denotes the unconditional correlation between labor productivity and hours worked, while $cor(\Delta z^{lp}, \Delta h|\varepsilon^T)$ and $cor(\Delta z^{lp}, \Delta h|\varepsilon^{NT})$ denote correlations conditional on technology and nontechnology shocks, respectively.

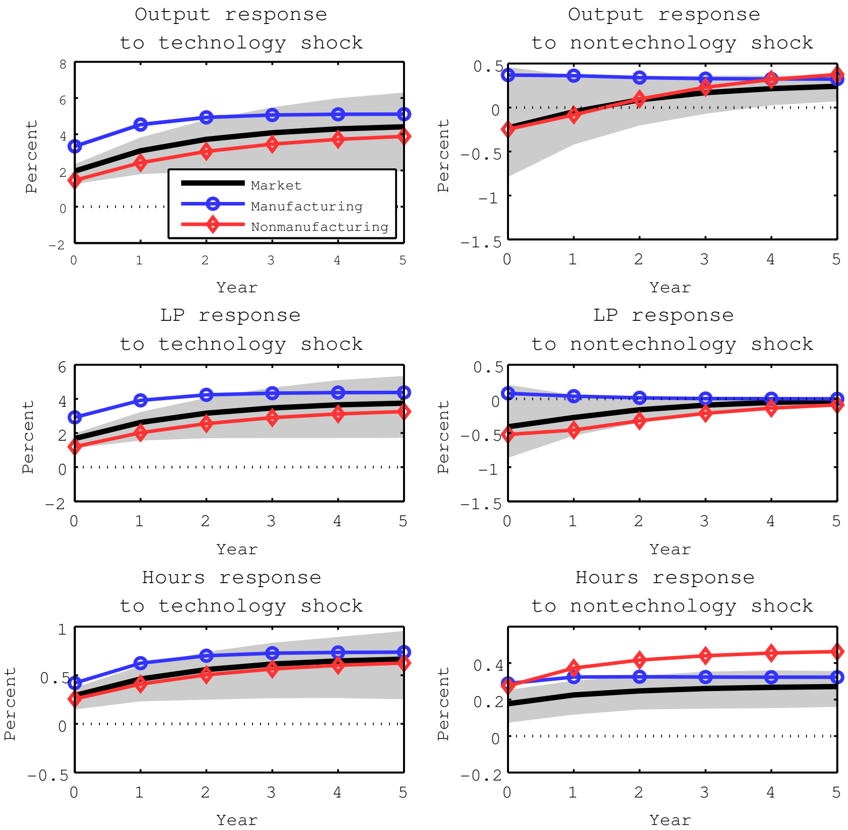


Figure A1. Impulse responses of output, labor productivity, and hours
Note: Labor productivity growth is used as the first dependent variable. LP denotes labor productivity.

Appendix C: Difference versus level

Christiano, Eichenbaum and Vigfusson (2003) argue that hours worked may be subject to overdifferencing. In other words, the response of labor input after a technology shock depends crucially on whether hours worked are assumed to be stationary. Therefore, we also report the result using the hours variable in levels. Figure A2 reveals that labor rises in response to positive technology shocks.

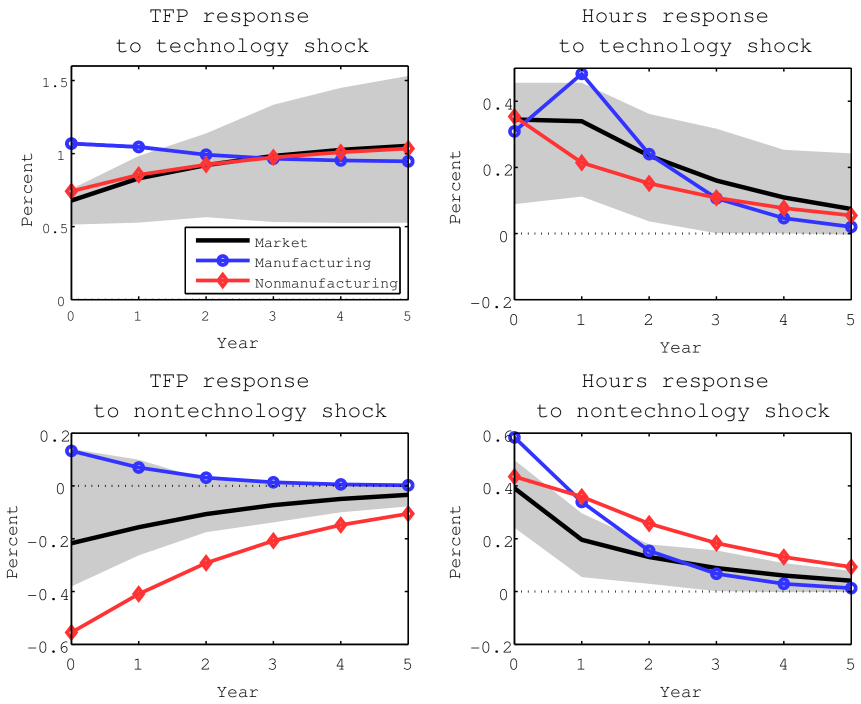


FIGURE A2. Impulse responses when estimating the VAR model using hours worked in levels.

Appendix D: Sign restriction identification

Braun and Shioji (2004) propose a VAR model with sign restrictions extending the model developed by Uhlig (2005). The advantage is that we can estimate the VAR model with all variables in levels. Following Braun and Shioji (2004), we assume that the response of productivity to nontechnology shocks must be very close to zero in the long run. The results are shown in Figure A3 and show that the increase in hours worked in response to positive technology shocks is insignificant.

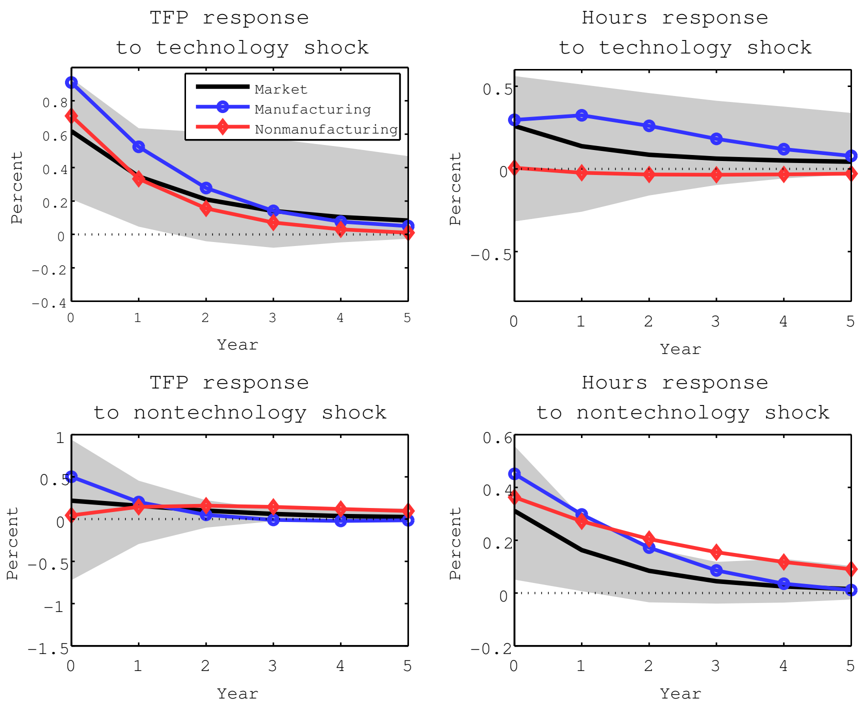


FIGURE A3. Impulse responses under sign restrictions.

Appendix E: Explanation of composition shocks

We explain the composition shocks using a simple general equilibrium model. As already discussed, composition shocks are assumed not to have a permanent effect on technology. Instead, they capture permanent changes in the composition of aggregate output or household preferences.

Households' utility function is given by

$$E_0[\sum_{t=0}^{\infty} \beta^t u(C_t, N_t)],$$

where E_0, β, C_t, and N_t denote the expectation operator, the discount factor, consumption, and labor supply, respectively. We assume that consumption takes a Spence-Dixit-Stiglitz-type aggregate form:

$$C_t \equiv \left[\sum_{i=1}^{28} \tilde{C}_{it}^{\frac{(\epsilon-1)}{\epsilon}} \right]^{\frac{\epsilon}{(\epsilon-1)}},$$

where i denotes the industry. The period budget constraint is

$$\sum_{i=1}^{28} P_{it}\tilde{C}_{it} + B_t = W_t N_t + (1 + R_t)B_{t-1} + \Pi_t,$$

where P_{it}, B_t, W_t, R_t, and Π_t denote the price index of industry i, bond holdings, the wage, the gross returns on bond holdings, and the ownership of firms, respectively.

Demand for industry i is assumed to follow

$$\tilde{C}_{it} = \omega_{it} \times C_{it},$$

where C_{it} denotes physical units of consumption in sector i, and ω_{it} is a composition shock that follows

$$\ln \omega_{it} = \ln \omega_{it-1} + \eta_{it}^{\omega},$$

where η_{it}^{ω} is a white-noise composition shock.

The production function of industry i can be written as

$$Y_{it} = \zeta_{it} N_{it},$$

where Y_{it} is output in industry i, ζ_{it} is technology, and N_{it} is the corresponding labor input. The productivity process follows

$$\ln \zeta_{it} = \ln \zeta_{it-1} + \eta_{it}^{\zeta},$$

where η_{it}^{ζ} is a permanent technology shock. We also assume that there is a industry-specific shock η_{it}^{S}. The long-run restrictions imply that η_{it}^{ζ} can influence the industry share and hence $\tilde{C}_{it}$ but η_{it}^{ω} cannot influence ζ_{it}:

$$\lim_{j\to\infty} \frac{\partial \zeta_{it+j}}{\partial \eta_{it}^{\omega}} = 0,$$

$$\lim_{j\to\infty} \frac{\partial \zeta_{it+j}}{\partial \eta_{it}^{S}} = 0,$$

$$\lim_{j\to\infty} \frac{\partial \tilde{C}_{it+j}}{\partial \eta_{it}^{S}} = 0.$$